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Emerging Architectures for Cognitive Neuroscience (CNS) Underwater Systems

Submarine Sonar Department

Naval Undersea Warfare Center Division
Newport, Rhode Island

Reprint of a paper and presentation given at the *NATO Advanced Study Institute on Computational Hearing*, 11 July 1998, Il Ciocco, Italy.

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14. ABSTRACT

This paper discusses initial efforts to understand and exploit Cognitive Neuroscience (CNS) for underwater systems. Compared to early sonars that used electro-mechanical compensator plates, underwater systems have benefited from automation using digital beamforming and signal processing introduced by modem electronics. Some of the evolving body of knowledge about CNS and how animal (including human) brains function has been converted into practical, computer-based demonstrations showing how to improve sonar signal processing. Additionally, we anticipate that a growing understanding of CNS will lead to even greater automation, perhaps even Fully Automated Systems Technology ??(FAST) concepts. FAST, in turn, will likely revolutionize sonar.

15. SUBJECT TERMS

Fully Automated Systems Technology; FAST; CNS; Cognitive Neuroscience Underwater Systems

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EMERGING ARCHITECTURES FOR COGNITIVE NEUROSCIENCE (CNS) UNDERWATER SYSTEMS[1]

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ABSTRACT

This paper discusses initial efforts to understand and exploit Cognitive Neuroscience (CNS) for underwater systems. Compared to early sonars that used electro-mechanical compensator plates, underwater systems have benefited from automation using digital beamforming and signal processing introduced by modern electronics. Some of the evolving body of knowledge about CNS and how animal (including human) brains function has been converted into practical, computer-based demonstrations showing how to improve sonar signal processing. Additionally, we anticipate that a growing understanding of CNS will lead to even greater automation, perhaps even Fully Automated Systems Technology (FAST) concepts. FAST, in turn, will likely revolutionize sonar.

1. INTRODUCTION

We report here on efforts to understand and exploit Cognitive Neuroscience (CNS) for application to underwater systems, in general, and to underwater acoustics, in particular. Some of the evolving body of knowledge about CNS and how animal brains function has been converted into practical, computer-based demonstrations showing how to improve sonars. An application of such a sonar is monitoring fish populations for treaty control. We anticipate that a growing understanding of CNS will lead to even greater automation; indeed, we feel that a "Grand Challenge" is to develop Fully Automated Systems Technology (FAST) concepts that will revolutionize sonar signal processing. This anticipation is driven by system needs and brain research that will be discussed in this article. Gazzaniga [9] expressed widely-held thoughts with these words: "At some point in the future, Cognitive Neuroscience (CNS) will be able to describe the algorithms that drive structural neural elements into the physiological activity that results in perception, cognition and perhaps even consciousness." The application of CNS to sonar systems is driven by a need to reduce the load on the sonar operator, to simplify the sonar's operation, indeed to even dramatically reduce the number of sonar operators while simultaneously maintaining or improving the sonar's performance in an increasingly complex environment. We expect to apply algorithms of some structural artificial neural elements such as sensory, motor, attention, memory, thought, and imagery systems into elements of a sonar system.

2. BACKGROUND

2.1 System Requirements

This paper is a summary of the current state of CNS work of scientists and engineers engaged in "Systems Research". These efforts are at the systems level and involve work across scientific disciplines. We summarize Systems Research in the initial stages of a multi-year examination of the implications of CNS on the design of sonars. We have focused on sonar systems, as a first logical step and intend to expand to other undersea systems including, for example, Autonomous Underwater Vehicles (AUVs), at a later date. We hope to understand how the brain processes data and investigate opportunities to use this information to improve sonars and other underwater systems. Several requirements will change the way the sonar operator interacts with underwater acoustic sensor systems. These requirements include:

- reducing the number of personnel,
- providing information, rather than processed data, to significantly reduce data evaluation time and thereby enhance the decision-making process,
- increasing sonar array size to improve detection which will, as a by-product, increase the sonar operator load, especially in cluttered acoustic environments, and

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[1] This paper is excerpted from a more extensive manuscript titled "Implications of Cognitive Neuroscience (CNS) for Use in Underwater Systems", authored by G. Clifford Carter, Lewis Meier, Walter L. Clearwaters, Roger Woodall, John Cooke, John V. Sanchis, James P. Shores, Azizul H. Quazi, Ivars Kirsteins, and Arthur S. Westneat, July 1997. Since original circulation was limited, we present here a condensed version suitable for wider distribution.

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[3] On assignment from University of Rhode Island, Kingston, R.I.

- increasing focus on reconnaissance connectivity which places new and complex demands on operators.

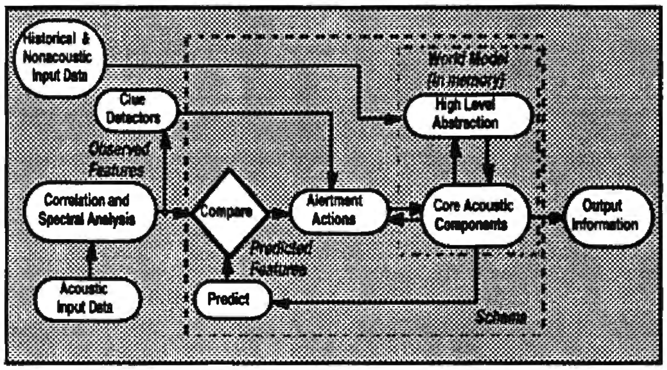

Figure 1. Diagram of a CNS sonar, modified from [6]. Note the use of feedback, memory, alertment, and a world model.

These requirements will force a sonar operator paradigm shift. This shift can be realized by further automation including taking advantage of highly developed computer models of how the brain functions. At this initial stage of our work, we seek to extend and apply these models:

(1) Scene Analysis (Bregman [3] and Wang [16]),
(2) Dynamically Stable Associative Learning (DYSTAL) (Vogl and Blackwell [15]),
(3) Adaptive Resonance Theory (ART) (Grossberg [10]),
(4) Microtubules (Hameroff [11]), and
(5) Automatic Salient Contour Extraction NeTwork (ASCENT) (Finkel [7]).

These models are a representative selection that we have found interesting and useful. We expect to include other models in our consideration as we become aware of them.

2.2 CNS Defined

Kosslyn and Koenig [14] give a detailed definition of CNS. A more comprehensive discussion and extensive compendium of papers is provided by Gazzaniga [9] in *The Cognitive Neurosciences.* Briefly, cognition is the process of perceiving and knowing. Neuroscience is the investigation of how the brain works using techniques and results from many disciplines. Thus, CNS is the combination of cognition and neuroscience in the investigation of how the brain performs the cognition process, including how it *perceives, learns, remembers, reasons, and satisfies goals.* Perceiving includes abstracting, classifying, generalizing, and synthesizing. Learning can be supervised or self-taught and includes cognitive learning. Remembering uses very short term, short term, long term, and associative memory. Reasoning involves making analogies, using common sense and prediction. Satisfying goals requires planning, decision making, and self-motivation.

3. Principles Drawn From CNS Related to Sonar Experimentation

The brain analyzes incoming acoustic data from the ears to extract sets of primitives, which are sensations that it cannot break into more primitive sensations. In auditory (visual) scene analysis, a primitive is a stream (visual object) that cannot be broken into parts. In Cooke's Ph.D. thesis [5], the primitives were synchrony strands. Features, in contrast, are properties of streams or objects that can be used to classify and group them. Features might include pitch, onset and offset. For example, Cooke uses pitch to group synchrony strands as coming from one acoustic source. The brain extracts primitives by measuring certain features of the incoming data using appropriate neural networks. Artificial neural networks attempt to emulate actual brain neural networks, weight, sum, then distort with a no-memory non-linearity. For a more detailed description see Chang, Bosworth, and Carter [4].

The human brain, through its complex evolution, appears to have followed some essential systematic principles. We hypothesize the following principles as the possible reasoning structure: Incoming data from sensors, including audio and visual is fragmented into essential elements called "primitives." Stored memories reside as elementary fragments located separately over regions of the brain's cortex. A memory location specific to a fragment is common to all concepts in memory that relate to that description. A neuronal process exists which matches and compares fragmentary components of data and memory. When sufficient preferential elements are present, the neuron fires announcing the rudiments of a concept for higher level assessment. A hierarchical analysis exists linking the fragmentation of data to alertment in the conscious mind. Neurons exhibit synaptic plasticity. Under special circumstances, dendritic growth can occur. The brain has feedforward and feedback mechanisms. The brain operates in a conscious (or alerted) and subconscious (or unalerted) mode. Trial solutions are attempted. When faced with a complex set of incoming data, the brain selects the response that provides a match consistent with all constraints.

4. MODELS OF THE BRAIN

In this section we report on five models of brain and sensor structure: (1) Scene Analysis, (2) Dynamically Stable Associative Learning (DYSTAL), (3) Adaptive Resonance Theory (ART), (4) Microtubules, and (5) ASCENT.

4.1 Scene Analysis

Scene Analysis includes visual and auditory components. Visual scene analysis is the separation of incoming light energy into a set of independent visual objects. Similarly, Auditory Scene Analysis (ASA) is the separation of acoustic energy into a set of independent sound sources. Both have potential in the design of improved sonar systems that use, for example, either automated ASA of beam-formed sonar signals or automated visual scene analysis of displayed sonar grams. Scene analysis detects primitives (sub-objects that cannot be further decomposed) and combines them to form visual objects or sound sources. While visual and auditory primitives are derived largely from neuroscience, high-level fusion or analysis is carried out using techniques from cognitive science. Neuroscience explains critical low-level visual processing in the brain and explains some facts about low-level auditory processing. For underwater acoustic applications, much low-

level auditory processing may be inferred from lower level visual processing. Recent advances in auditory processing include the Ph.D. thesis by Ellis [6] on ASA.

Ellis [6] states that his thesis "presents a collection of components assembled into a partial model that mimics some of the aspects of auditory information processing." His thesis is comprised of two notions: "perception proceeds via ... reconciliation of the internal representation with the perceived (sensed) signal from the external world" and "the full spectrum of "real" sounds are adequately spanned by the combinations of a few simple parameterized sound primitives." The Ellis thesis is then "prediction-driven" unlike the ASA data-driven models of Cooke [5] and others that grew out of Bregman [3]. Ellis develops a model of the mind that is constantly trying to reconcile what it hears with what it expects, it then becomes alerted by unexpected sounds.

4.2 Dynamically Stable Associative Learning (DYSTAL)

DYSTAL is a class of biologically plausible artificial neural networks based on studies of the nervous system of the marine snail Hermissenda crassicornis and the hippocampus of rabbits. (See Alkon [2] and Irwin [12]. For other hippocampus work, see also Japkowicz, Myers, and Gluck [13].) DYSTAL networks, unlike standard artificial neural networks, use non-Hebbian learning rules, are self-organizing, converge monotonically, have large capacity and linear complexity and require few training samples. A DYSTAL network learns to associate conditioned stimulus input patterns with unconditioned stimulus patterns, demonstrating the association by outputting the appropriate unconditioned stimulus pattern in response to each conditioned stimulus input pattern alone. Both conditioned and unconditioned stimuli are vectors. A DYSTAL network has input neurons for each component of these vectors and an output neuron for each component of the unconditioned stimulus. Connecting each output neuron with its corresponding input unconditioned stimulus neuron and all conditioned stimulus neurons is a set of patches, which are vectors that act as hidden neurons. Prior to training, no patches exist. During training, DYSTAL compares conditioned-stimulus/unconditioned-stimulus pairs with existing patches. If any existing patches match the stimuli sufficiently, the most similar patch for each output neuron will determine its output. DYSTAL updates each such selected patch by averaging its stored patch vector with appropriate components of the stimuli. Otherwise, DYSTAL creates a new patch for each output neuron using the appropriate components of the stimuli.

In a presentation at NUWC on DYSTAL, Vogl and Blackwell described how they have reverse engineered the brain to achieve pattern recognition comparable to that of human observers. Details of the research were beginning to emerge in the *Biological Cybernetics* pattern recognition publication by Alkon, Blackwell, Barbour, Rigler, and Vogl [1]. One experiment involved using the picture of a face. In the experiment comparing the DYSTAL algorithm to humans, humans slightly outperform DYSTAL under very low noise conditions but DYSTAL outperforms humans (in the important case) when high noise levels are present, a case of interest in underwater applications.

4.3 Adaptive Resonance Theory (ART)

Grossberg, the father of ART, provides the following acoustic example (See Grossberg [10].) "Suppose that you hear a noise followed by the words "eel is on the ..." If followed by the word "orange," you hear "peel is on the orange." If followed by the word "wagon", then you hear "wheel is on the wagon." Thus it appears the brain can work "backward in time." Grossberg's theory is that the brain's neural network resonates for a short while until it can resolve this uncertainty. Freedman (See Freedman [8]) explains: " ... ART--which stands for 'adaptive resonance theory' -- ... consists of four main components: a short term memory ... a long term memory ... an attentional subsystem to focus attention ... and a reorienting system ... unlike other neural networks, ART doesn't depend on an outside supervisor to tell it if its guess was right ... ART generally blows away the competition: in applications for which back-prop networks require 20,000 supervised training rounds ... ART teaches itself in 5 rounds ... rivaling human performance ... " Others would argue that this is an overly optimistic assessment of ART and that its success is situationally dependent; moreover, that competitive methods, including artificial neural networks with back propagation and more advanced versions of ART are needed to begin to rival portions of human brain performance.

4.4 Microtubules

Microtubules are being modeled as small computers within neurons. Freedman [8] discusses Microtubules; he states: " ... microtubules – thin cylinders of protein molecules that lend internal structure to neurons ... each neuron's microtubule network in effect comprises a powerful, high-speed internal computer." Freedman quotes researcher S. Hameroff as stating: "Neurons produce a yes-or-no decision but a lot of thinking goes into that decision. Microtubules could be the primary processing element in the brain." Freedman goes on to suggest that: "The existence of microtubular intelligence within neurons would be exceedingly bad news for any researchers who hope to construct an artificially intelligent device out of conventional computer hardware." Hameroff believes that "The complexity of neurons ... are closer to entire computers than individual switches. This implies the mechanism of consciousness may depend on an understanding of the organization of adaptive ('cognitive') functions *within* living cells." Hameroff calculates that at the current rate of progress, semiconductor technology will produce a computer capable of human-brain-like raw processing power .. within the next few decades ... (but) if each neuron has sophisticated internal processing network based on Microtubules, he claims, then the semiconductor computers of the early Twenty-First century will fall short by a factor of more than a billion. While we continue to find evidence that there are sub-neuron computations that are necessary and at work, we have not yet found the experimental evidence that mircotubules are the computational machines hypothesized.

4.5 ASCENT

ASCENT (Automatic Salient Contour Extraction NeTwork) [7] is a biologically plausible neural network based upon the human visual processing system that is capable of extracting salient contours from real images.

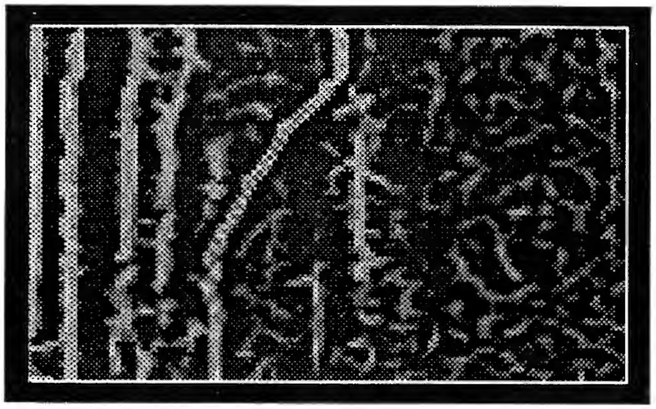

Figure 2. Modeled after the human visual processing system, ASCENT extracts salient contours from an actual BTR display

It has been used to extract tracks from a Bearing-Time Recorder (BTR) display as is shown in Fig. 2. In modern sonars operators must page through many similar displays of the acoustic scene. Often, for example, these are frequency-time plots of acoustic power displayed for each of numerous bearings. Automated methods such as ASCENT offer the potential to replace human operators with Fully Automated Systems Technology (FAST) operators.

5. CONCLUSIONS

Advances in CNS have been and will continue to be important to Fully Automated Systems Technology (FAST) including sonar signal processing. Indeed, biologically inspired architectures, even if not precise models of the actual biology can suggest new sonar processing approaches to automation.

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Emerging Architectures for Cognitive Neuroscience (CNS) Underwater Systems

by
G. Clifford Carter and G. Betancourt

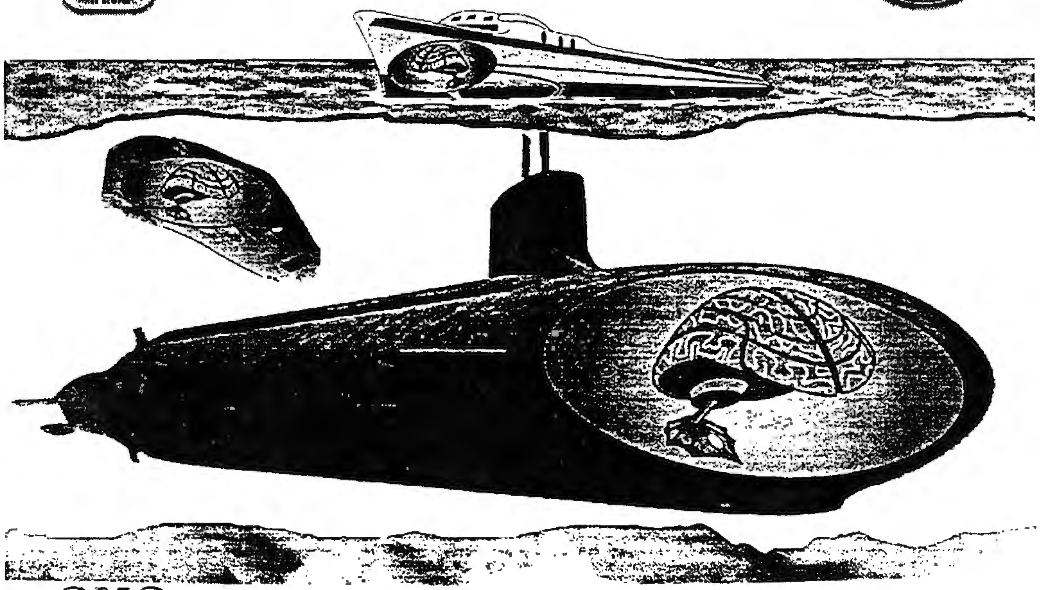
CNS Sonar is Part of
Fully Automated System Technology (FAST) Program

NATO ASI on
Computational Hearing
Il Ciocco, Italy
11 July 1998

Presented by:
Dr. Cliff Carter

CNS FAST GROUP

Computational Hearing Underwater



CNS FAST GROUP

Purpose

Introduce the Audience to:

- What the *computational underwater hearing*, that is, sonar community has learned about Cognitive Neuroscience (CNS)
- *What research needs to be done*

CNS FAST GROUP

NUWC's CNS Technical Leaders
(CNS = Cognitive Neuroscience)

8 JUA co-authors

Dr. Cliff Carter, Sub Sonar
John Cooke, Surface Sonar
Dr. Ivars Kirsteins, Surface Sonar
Dr. Lew Meier, Sub Sonar
John Sanchis, Sub Sonar
Dr. James Shores, Sub Sonar
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Dr. Y. Masakowski, Combat Control
Chris DeAngelis, Combat Control
Dr. Richard Katz, Surface Sonar
Dr. Roy Streit, Combat Control
Dr. Susan Kirschenbaum, Combat Control

Consultants

Walter Clearwaters
Prof. Arthur Westneat
Gerson Betancourt, URI

CNS FAST GROUP

Human Brains

- *Process acoustic signals* with reasoning and learning
- Are systems with (sensory) inputs and (motor) outputs
- Are complex systems that are nonlinear and time-varying
- Have short-term and long-term memory organized with schema based world model
- Have slowly-changing architectures (synaptic plasticity)
- Have automatic (subconscious) and controlled (conscious)
- Can nonlinearly redirect attention in response to stimulation
- Have a massively parallel architecture with extensive feedback
- Contain 10 - 100 billion neurons
  - → with 1,000 - 10,000 connections to other neurons
  - → with nonlinear and time-varying
  - → with sub-neuron microtubule structure
- Show evidence of resonating at 40 Hz
- *Form the biological inspiration for useful computational models*

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Cognitive Neuroscience Network Models

- Dynamically Stable Associative Learning (DYSTAL), T. Vogl [1995], GMU
- WRENN constructed neural net for ATR, R. Woodall [1994], NUWC
- Sub-Neuron Microtubules increase processing power, S. Hameroff, UAz
- ASCENT human vision model, for NUWC BTR data, L. Finkel [1994], UPenn
- Synaptic LTP exceeded conventional sonar, R. Granger [1994], UCI
- Adaptive Resonance Theory (ART), S. Grossberg, G. Carpenter [1995], BU
- Hardware, A. Maren [1995], Accurate Automation Corporation (AAC)
- Streit's Probabilistic Neural Network (SPNN), R. Streit [1991], NUWC
- Automatic Target Recognition Neural Net H/W, L. Cooper, Brown U
- Neurally Inspired Contact Estimation (NICE), C. DeAngelis [1995], NUWC
- Auditory Scene Analysis (ASA), A. Bregman
- Data-Driven Computational ASA (CASA), Cooke, Brown, Klassner
- Prediction-Driven CASA, Ellis
- Top-Down Hybrid Convergent Model, W. Clearwaters, A. Westneat et al.

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Apply CNS to Meet the Underwater Acoustic Technical Challenge

Traditional sonars:

- Rely heavily on human sight and hearing
- Overload and tire human operators
- Are not capable of handling more acoustic inputs
- Leave information extraction to human operators
- Have labor intensive displays (e.g., BTR)
- Require manual (human) classification

Today's sonars met yesterday's needs, but will not meet tomorrow's needs

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Initital Objectives

- Extend CNS and Computational Hearing to underwater acoustics / sonar
- Develop a specification and evaluation criteria for FAST CNS sonar
- Design, build, and test a *revolutionary* computational sonar that *emulates CNS human-brain functions*

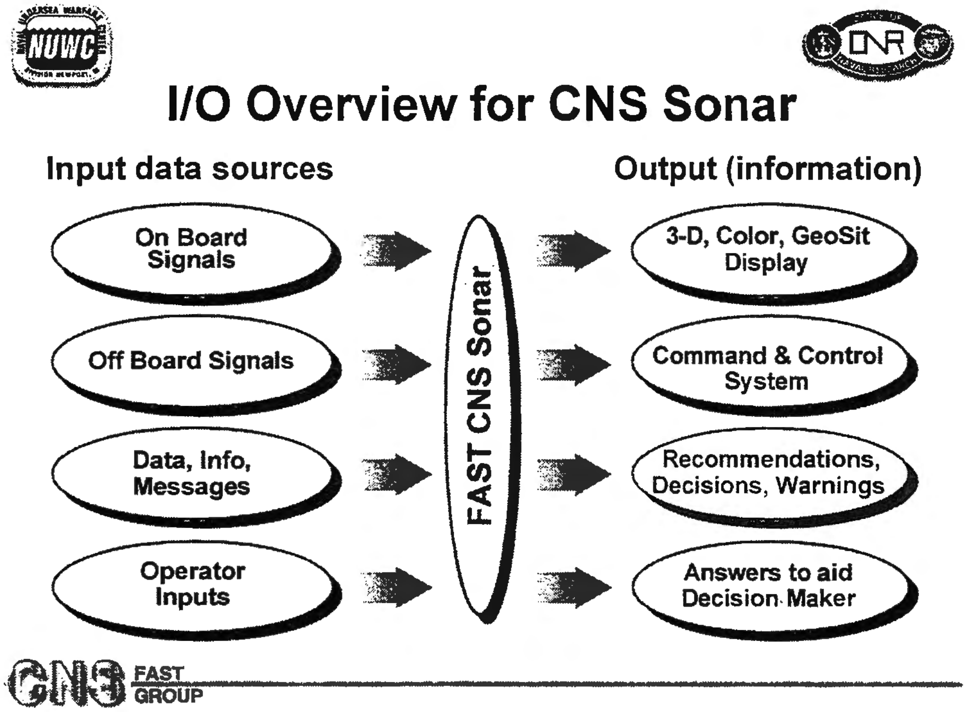
CNS FAST GROUP

Our Vision:

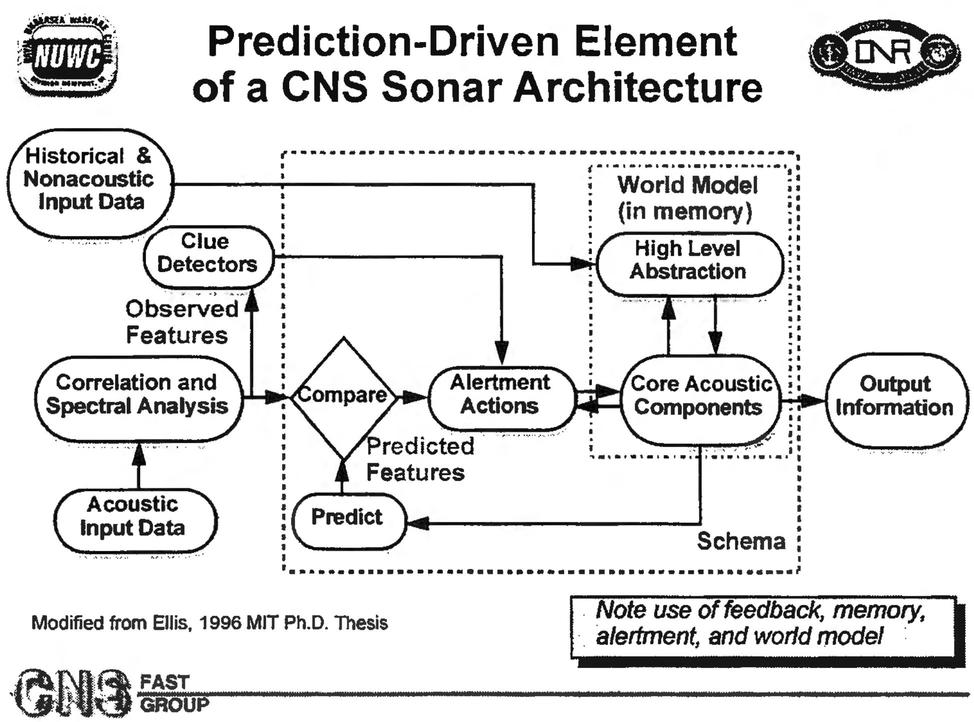
A Revolutionary CNS Sonar that will:

- *Replace human sonar operators* with fully automated "silicon-based" assistants that recommend timely decisions with expert or "ace" abilities to a human machine supervisor
- Perform well in new acoustic environments
- Handle an order of magnitude more acoustics
- Fuse, compress, & merge data into information
- Display needed information in the right format, to the right decision maker, at the right time
- *Adapt to new tasks by learning & reasoning*

CNS FAST GROUP

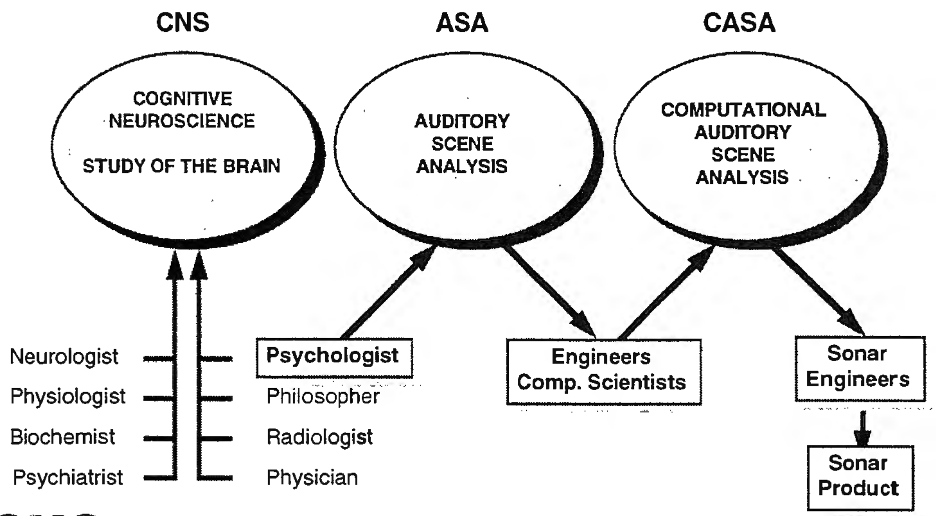


NUWC
ONR
I/O Overview for CNS Sonar
Input data sources
Output (information)
On Board Signals
Off Board Signals
Data, Info, Messages
Operator Inputs
FAST CNS Sonar
3-D, Color, GeoSit Display
Command & Control System
Recommendations, Decisions, Warnings
Answers to aid Decision Maker
CNS FAST GROUP



NUWC
Prediction-Driven Element of a CNS Sonar Architecture
ONR
Historical & Nonacoustic Input Data
Clue Detectors
Observed Features
Correlation and Spectral Analysis
Acoustic Input Data
Compare
Predicted Features
Predict
Alertment Actions
World Model (in memory)
High Level Abstraction
Core Acoustic Components
Output Information
Schema
Modified from Ellis, 1996 MIT Ph.D. Thesis
Note use of feedback, memory, alertment, and world model
CNS FAST GROUP

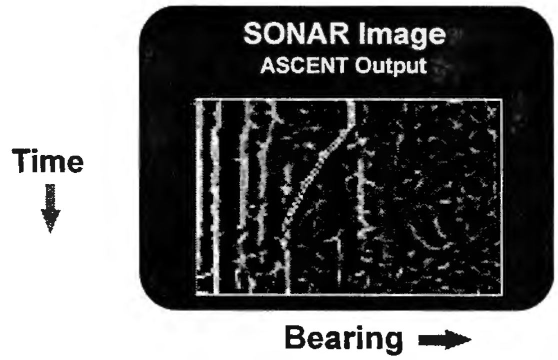
CASA: Developing a CNS Architecture



Technical Status

- Identified need and *FULL AUTOMATION GRAND CHALLENGE*
- *Published JUA article* on CNS Implications to sonar
- Completed study of Computational Acoustic Scene Analysis (CASA); Arthur Westneat, 1997
- Analyzed Prediction-Driven CASA (Ellis, 1996 MIT Ph.D. Thesis) that *extended Cooke's Data-Driven CASA approach*
- Extended sub-neuron work of Prof. S. Hameroff to more completely explain brain functions
- Developed basis for showing Artificial Neural Networks (ANNs) achieve Maximum Likelihood (optimum) performance (R. Streit)
- Applied Prof. L. Finkel ASCENT algorithm to sonar BTR data
- Met with small business building ANNs (L. Cooper, Nobel Laureate and *Dr. A. Maren, Accurate Automation Corporation*)
- Held workshop on CNS Sonar

Preliminary Results of Applying ASCENT Algorithm to Bearing-Time Recorder (BTR) Data



Results with Dr. Finkel, UPENN demonstrate full automation of visual display of acoustic data

- Modeled after the human visual processing system
- ASCENT extracts salient contours from a real BTR display

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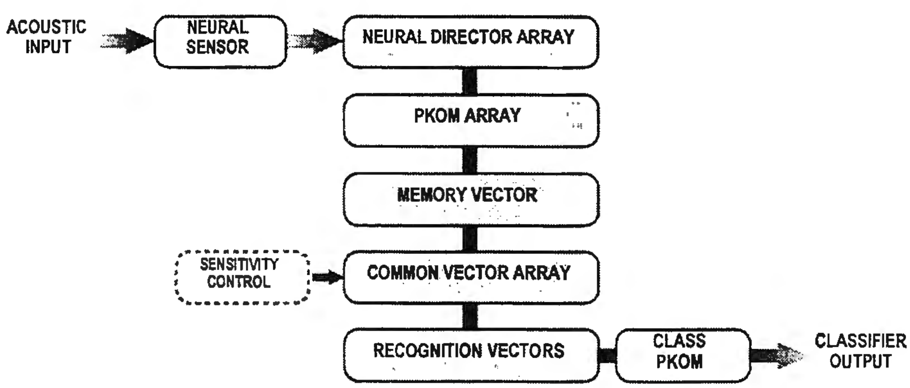
WRENN Neural Network Architecture



PKOM = Position King of the Mountain (Winner Take All)

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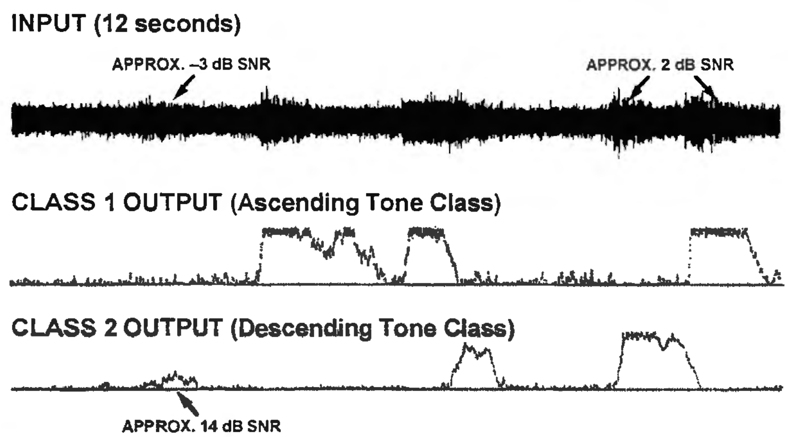
Results of Successfully Applying WRENN Algorithm to Underwater Porpoise Data



CNS FAST GROUP

Open Technical Questions

- How do we test & evaluate
  →a complex time-varying, nonlinear system?
  →learning, reasoning, and adaptability?
- What extensions are required to CNS to build a CNS sonar?
- How would we demonstrate a FASTWAR CNS sonar?
- How does the internal architecture change with time?
- Is problem scaleable? Is a CNS sonar demonstrable in small system? Or does it take a large system? How many neurons should be in the first phase test bed sonar system?
- What are appropriate architectures for our CNS sonar?
- How will we "program" our CNS sonar?
- How will our CNS sonar learn?
- How and at what data rates will we stimulate sonar?
- How does our CNS sonar implement the subconscious (automatic) and conscious (controlled) mind?

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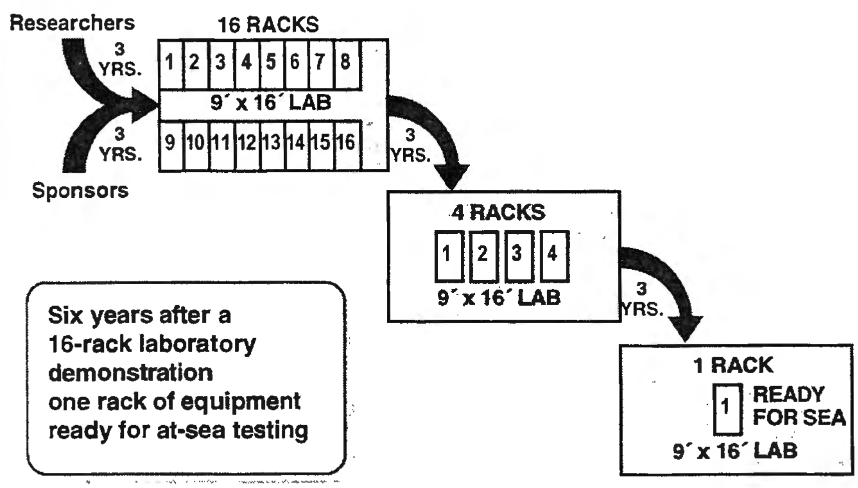
Implications of Moore's Law



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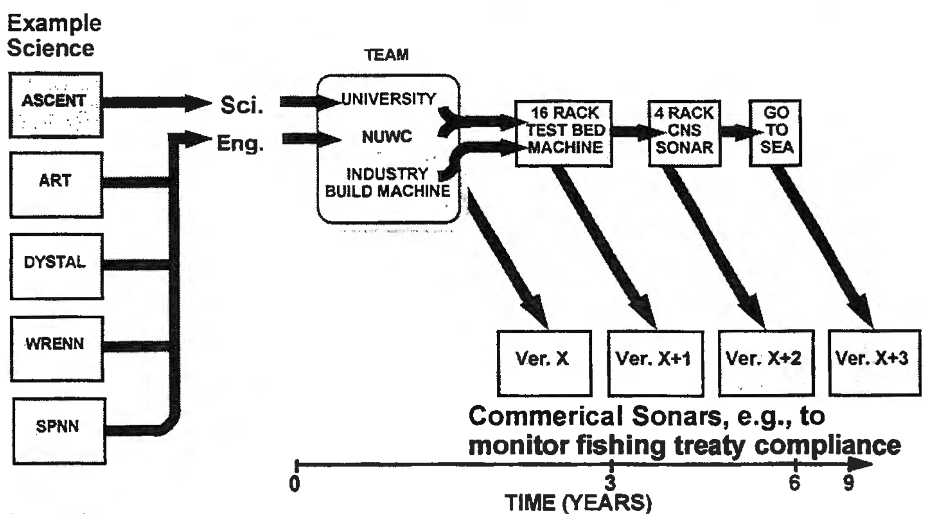
Conceptual Program (Timeline)



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Overview of CNS Thrusts

TOPIC	NUWC Lead	Partner
• CNS Systems	Clearwaters	UNH (A. Westneat) / NUWC (Keil)
• ASCENT	Carter	UPENN (L. Finkel) / ONR (Hawkins/Davis)
• JONESY	Masakowski	T.B.D. / CNO (Morgan)
• START	Shores	BU (G. Carpenter) / ONR (Hawkins/Harned)
• CASA	Meier	VU (F. Klassner) /OSU (D.Wang)
• NOSIP	Quazi/Katz	MIT (C. Poon) / ONR (Davis)
• TSA	Kirsteins	URI (R. Kumerasean) / ONR (Gisiner)
• AAC/CMA	Streit	T.B.D. / DARPA (Munoz)
• GUS	Masakowski	GaTech (T. Doll) / CNO (Hanlon)
• World Model	Aaron	T.B.D.

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Project:
CNS Systems

NUWC leader(s):
W. Clearwaters & CNS FAST Group

Team Members:
A. Westneat, UNH, various universities, and industrial partners

Technical Issues:
Can we demonstrate automatic and cognitive machine processing as a first step towards Fully Automated System Technology (FAST)?

Objective:
Develop several CNS systems based upon human brain architecture

Payoff:
Revolutionary underwater systems that cognitively and automatically handle ten times the volume of data

Milestones:
T.B.D.

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Project:
GTV User System (GUS)

NUWC leader(s):
Dr. Yvonne R. Masakowski

Team Members:
Dr. Theodore J. Doll, GA. Tech
Dr. G. Clifford Carter, NUWC

Technical Issues:
Development of intelligent expert systems based on perceptual expertise of operators

Approach:
Investigate GaTech Vision (GTV) simulation as an automatic recognition system

Objective:
Enhance sonar displays, and operator training and performance

Payoff:
Improved recognition & classification of sonar imagery in cluttered environment in decreased amount of time

Milestones:
- Comparative report on developed displays
- Briefing and video tape demo of GUS
- Transition to sonar system

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Project:
ASCENT

NUWC leader(s):
Dr. Cliff Carter, NUWC

Team Members:
Dr. Lew Meier, NUWC
Dr. Leif Finkel, UPENN

Technical Issues:
- Implications of display thresholding on performance
- Output interface for display tracks

Objective:
Extend human eye research to automatically recognize sonar displays with human ability

Payoff:
Reduce the number of sonar operators by factor of 3 while handling 10 times the data

Milestones:
- Test and Evaluation Algorithms
- Refine Algorithms, Evaluate Performance
- Transition to sonar product

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Project:
Tonotopic Signal Analysis (TSA)

NUWC leader(s):
Dr. Ivars Kirsteins

Team Members:
Prof. R. Kumaresan, URI
Dr. J. Fay, NUWC
Dr. S. Mehta, NUWC

Technical Issues:

- Development of mathematical algorithms
- Representation of radiated signatures
- Robustness to noise
- Classification performance gains

Objective:
Human listener-like capability for characterization and classification of radiated signatures

Payoff:
Significantly improved passive sonar multi-sensor detection, classification, localization, and data fusion

Milestones:

- Development of mathematical steps and application to sea state
- Demonstration using sea data
- Transition to sonar product

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Project:
JONESY

NUWC leader:
Dr. Yvonne R. Masakowski

Team Members:
Dr. Susan S. Kirschenbaum, NUWC
Mr. John Cooke, NUWC

Technical Issues:
Development of intelligent entropic system based on extrapolating perceptual strategies of expert operators

Objective:
Enhance displays & training based on perceptual expertise of sonar operators

Payoff:
Reduced training time
Decrease in decision time
Enhanced human performance

Milestones:

- Develop displays with strategies or perceptual of expert
- Test effectiveness of new training system
- Implement advanced training system

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Project:
World Model

NUWC leader(s):
Dr. Arnold Aaron

Team Members:
Dr. John Salisbury, A&T

Technical Issues:
Database Architecture for Cognitive Systems

Objective:
Put knowledge into accessible form

Payoff:
Rapid, automated environmental corrections
Multi-contact resolution
Reduced time

Milestones:
T.B.D.

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Project:
Nonlinear Signal Information Processing (NOSIP) for CNS Sonar

NUWC leader(s):
Dr. Azizul H. Quazi
Dr. Richard Katz

Team Members:
Dr. C. Poon, MIT
Dr. C. Baker, UNC
Dr. J. Salisbury, A&T

Technical Issues:
- Estimation of Joint Density function
- Robustness of nonlinearly invariant measures

Approach:
- Nonlinear correlation based on information theory

Objective:
Extend nonlinear signal information for enhanced acoustic detection, classification, and localization

Payoff:
Improved acoustic classification and localization in USW

Milestones:
- Collect sea data and generate simulated signals; analyze data
- Develop algorithms
- Transition to sonar system

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Project:
CASA in Undersea Environments

NUWC leader(s):
Dr. Lewis Meier

Team Members:
Mr. Art Westneat, UNH
Dr. Dan Ellis, UC-Berkeley
Dr. De Liang Wang, Ohio State
Dr. Frank Klassner, Villanova

Technical Issues:

- What CASA based algorithms and heuristic procedures are useful in undersea systems?
- What hardware and software architecture are best to implement these algorithms?

Objective:
Augment existing systems so human operator can perform:

- Existing tasks better
- New tasks

Payoff:

- Provide the operator with information displays of the acoustic scene
- Extend the systems ability to classify a wider range of targets

Milestones:

- Implement existing CASA systems at NUWC
- Test with simulated and real underwater signals
- Modify CASA systems
- Demonstrate CASA at sea

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Project:
Early Cognition Model for ACC / CMA

NUWC leader(s):
Dr. Roy L. Streit

Team Members:
T.B.D.

Technical Issue:
Validate the analogy that multi-sensory integration is to passive ACC as early cognition is to CMA

Objective:
Demonstrate joint Acoustic Contact Correlation (ACC) and Contact Motion Analysis (CMA) processing based on mulit-sensory integration and early cognition

Payoff:
Superior automated joint ACC/CMA performance when compared to current non-integrated hierarchical approach of first ACC, then CMA

Milestones:

- Develop CNS Algorithms
- Test, refine, demonstrate
- Transition to advanced demo

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Project:
START

NUWC leader(s):
Dr. James P. Shores (NUWC)

Team Members:
Mr. Gerson Betancourt, URI
Dr. G. Carpenter, BU

Technical Issues:

- Will ART be applicable to underwater acoustic signals?
- What gain is provided?

Objective:
Extend Adaptive Resonance Theory (ART) to demonstrate Sonar Transient Adaptive Resonance Theory (START) classification

Payoff:
Improved accuracy and speed of classification with full automation

Milestones:

- Install in sonar lab
- Test with sea data
- Transition to sonar

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Summary

- Problem
  - → Unknown / unpredictable acoustic tasks
  - → Variable & complex ocean acoustic environments
  - → Today sonar operators are overloaded with data
  - → Future sensors and communications with off-board sensors will further increase acoustic load
- Solution
  - → Exploit and extend emerging knowledge of brain and Cognitive Neuroscience (CNS)

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Conclusions

- **Making progress understanding and extending Cognitive Neuroscience (CNS) to Sonar**
- ***Offering Researchers an opportunity to form cooperative partnerships with NUWC*** **to advance Fully Automated System Technology (FAST) Cognitive Neuroscience (CNS) Sonar Research & Development**

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Emerging Architectures for Cognitive Neuroscience (CNS) Underwater Systems

by

G. Clifford Carter and G. Betancourt

Traditional sonars:

- **Rely heavily on human sight and hearing**
- **Overload and tire human operators**
- **Are not capable of handling more acoustic inputs**
- **Leave information extraction to human operators**
- **Have labor intensive displays (e.g. BTR)**
- **Require manual (human) classification**

Fully Automated System Technology (FAST) **CNS Sonars are described at the poster session**

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